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SELECTED METHODS OF MEASURING OF TECHNOLOGICAL PROGRESS

Technological progress is a common phenomenon to be encountered on daily basis and in different aspects. Technological progress is perceived as a combination of quality changes in manufacture and services along with accompanying organisational changes. They are result of innovation that is brought about by various institutions on different economic levels. Research institutions and academic centres conduct basic research, R&D institutes concentrate on applied research and there is also development and implementation work relating to the sphere of economic practice. An alternative to conducting own research is to purchase patents and licences that can also be a driving force behind the development and is often less expensive.

There are various classifications of technological progress. The most useful seems to be the division between three kinds of innovations namely process, product and organisational innovations. The first type concerns the sphere of manufacture and relates to modernisation of the production facilities substituting labour with equipment of different mechanisation and automation degree. Product innovations concentrate on changing quality of goods and services by means of their modernisation or by launching new products. Organisational innovations involve the whole range of activities aiming at increasing efficiency of manufacturing and distribution, efficiency being an inherent element of technological progress[1].

A broad concept of technological progress and its effects makes this phenomenon very difficult to measure. The GUS (Polish Central Statistical Office) carries out studies and publishes detailed information on it. They concern for example the efforts made by companies to finance R&D, effects brought about by mechanisation and automation of production processes or modernisation of goods and services. On the one hand such diversity is an advantage as it allows for analysis of different aspects of technological progress,

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[1] Issues concerning technological progress are discussed in numerous monographs, and a concise summary is also given by G. Juszczak-Szumacher [1996].

but on the other it is a disadvantage if we want to make a thorough analysis of this phenomenon.

This study shows how to reduce a number of characteristics of technological progress with the use of taxonomic methods and factor analysis. One approach allows us to construct a synthetic measure based on detailed characteristics or to measure a distance between two comparable objects. The other approach reduces the original set of indicators to a group of factors that provide the best explanation for the variability of the phenomenon within the studied group of objects. Having the synthtetic measure(s) of technological progress we can use it in regression analysis to explain the influence of this phenomenon on the total economic activity or some of its aspects (for example foreign trade or labour productivity). The both presented methods should be perceived as an example of approaches that give a broader picture of technical progress when compared with detailed characteristics published by GUS.

1. Taxonomic methods

Taxonomic methods enable us to compare a set of objects characterised with many features. The basis for calculations is the observation matrix of k value of diagnostic features in n number of objects: $X = \lfloor x_{ij} \rfloor$ (i = 1, 2, ..., n; j = 1, 2, ..., k). Each matrix row includes observations on all diagnostic features in a given object whereas each column is a set of values of a given diagnostic variable (characteristic) in all studied objects[2]. In this analysis of technological progress objects can be understood either as periods of certain time intervals, as sectors of economy analysed in a given period of time or as the same sectors studied in different periods of time.

1.1. The construction of the synthetic measure

Characteristics of comparable objects are expressed in various units of measure. In order to establish the synthetic measure they need to be transformed in a way that would enable comparability. Among methods of such conversion are standardization and normalization (see: Nowak E. 1990). Standardization is a conversion where the arithmetic mean of a feature value evaluated for all objects is subtracted from a feature value in i -th object and the difference is divided by the feature standard deviation. This gives us transformed values which are expressed in standard deviation units. Normalization is a transformation

[2] Selection of diagnostic features for a comparative analysis of objects is quite problematic. Various methods are used for this purpose e.g. Hellwig's parametric model [1981].

where the original feature value is divided by the normalization factor which can be an average, maximum or minimum feature value or a feature value of any object from the studied set.

With the use of the transformed feature values you can construct the synthetic measure applying model or non-model method, the other being easier. It requires all transformed features to be of the same character i.e. to be either stimulants or destimulants. Therefore our first step is transformation of destimulants into stimulants as this is more natural synthetic measure for technological progress whose higher values will indicate better position of an object. A synthetic measure can then be an expression that is an arithmetic mean of normalised feature values:

$$S_i = \frac{1}{k}\sum_{j=1}^{k}\frac{x_{ij}^*}{\overline{X}_j} \quad (1)$$

where:

S_i – synthetic measure for i-th object,

x_{ij}^* – value of j-th feature (as stimulant) in i-th object,

$\overline{X}_j$ – arithmetic mean of j-th feature determined for all objects.

Empirical studies carried out with the use of a measure defined with formula (1) concerned three-year period 1999–2001 and a comparison of 22 branches within the section of industrial processing. The set of objects amounted to 66 units. Each object was described with 10 features that determine different aspects of technological progress. The choice of these characteristics resulted from accessibility of data base, published by GUS. The features were as follows:

- share of new and modernised goods in overall production value (in %),
- computer controlled systems (in units),
- machining centres (in units),
- industrial robots and manipulators (in units),
- automatic production lines (in units),
- computer-controlled production lines (in units),
- capital expenditure on R&D (in mln zl),
- expenditure to purchase ready-made technology (in mln zl),
- expenditure on marketing new products (in mln zl),
- expenditure on machines and technical equipment (in mln zl)[3].

[3] There are not all characteristics published by GUS, but other data refer only to individual years. The set of 10 features was a maximum option to choose for the studied period. The presented chracterictics are absolute numbers because characteristics of automation of fixed assets

The above calculation of the synthetic measure allows for its clear interpretation. Its values are around 1 that is an average value of the synthetic measure for the whole section in the studied period. And so $S_i < 1$ indicates progress in i-th branch below average and consequently if $S_i > 1$ it means that i-th branch is above average. The breakdown of all values of the synthetic measure is given in the annex. S_i values for the two poorest (manufacture of basic metals and textile industry) and two best branches (manufacture of machinery and equipment and medical instruments) are depicted in Fig. 1.

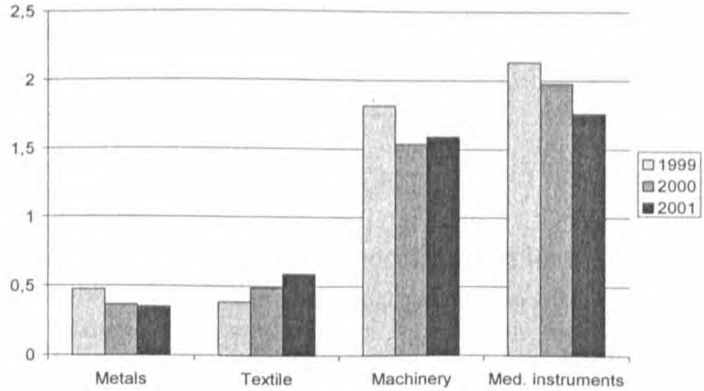

Fig. 1. Comparison of synthetic measures for chosen branches
S o u r c e: Own elaboraton.

Relations between determined values of the synthetic measure of "end" branches are significant. It is also interesting that in various branches changes go in different directions in time. In case of textile industry the synthetic measure has a rising tendency whreas in manufacture of medical instruments a considerable fall of the value can be observed.

1.2. Analysis of similarities between objects

Taxonomic methods also allow to determine a distance between objects described with various features. T. Michalski [2002] points out to two types of distance, both of which show differences in absolute values of characteristics and emphasize structure differences. The appropriate measures can be defined as follows:

are divided by gross value of fixed assets in constant prices whereas the value of outlay was referred to the production sold in a given branch.

– similarity of level of objects s and q

$$d(s,q)=1-\frac{1}{2\sqrt{kn}}\sqrt{\sum_j\left(z_{sj}-z_{qj}\right)^2} \tag{2}$$

where: $z_{ij}=\frac{x_{ij-\bar{x}_j}}{S_j}$ is a standard feature value,

– similarity of structure of objects s and q

$$\mu^*(s,q)=\frac{1+\mu(s,q)}{2} \tag{3}$$

where: $\mu(s,q)=\frac{\sum_j z_{sj}z_{qj}}{\sqrt{\sum_j z_{sj}^2}\sqrt{\sum_j z_{qj}^2}}$.

Both measures are set in interval <0,1> which makes their interpretation easier.

Similarities between objects were determined for characteristics observed on macroeconomic level in 1990–2001, objects being consecutive years. Detailed indicators of technological progress (features) are different for the whole economy than those used for the analysis of the production sector. On macroeconomic level R&D basic and applied research is analysed whereas in case of industry more emphasis is put on implementation. Macroeconomic characteristics mainly include a number of issued patents and inventions claimed in different classifications.

The set of features for research carried out in 90s was assigned three measures i.e. the synthetic measure of technological progress as given in a formula (1), level similarity measure (2) and structure similarity measure (3). For the synthetic measure a dynamics index was defined as year 1990 = 1 whereas similarity measures were calculated for consecutive years in comparison with the year 1990. In the first sample year all measures equal 1 as it is shown in Fig. 2.

The value of the synthetic measure for all years is below the level of 1990. The biggest drop noticed in 1993 is not suprising given a decline of economic activity at the beginning of the 90s. In consecutive years S_i dynamics gradually increases only to fall dramatically in 2001. The level similarity achieved the lowest value at the end of the sample period and the structure similarity in 1995. In Fig. 2 we can notice that two of the three measure values converge in the last year.

However the picture we get is pessimistic as for chances for development of our economy and its competitiveness on the EU market. Technological progress is the most important driving force behind this development and if we neglect financing it the gap between Poland and the poorest EU countries will only widen.

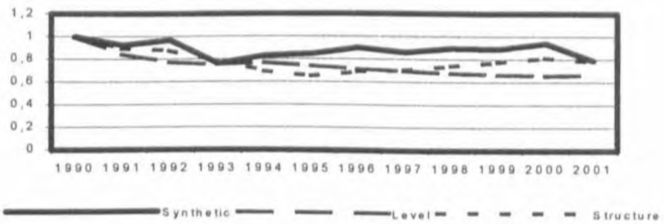

Fig. 2. Comparison of changes in the synthetic measure for technological progress along with level and structure similarity measures

Source: As same as Fig. 1.

2. Factor analysis

In this analysis a set of features describing objects is substituted by a smaller number of unobservable factors. It is assumed that each original feature is a linear function of m common factors and one specific factor that can be represented in a following system of equations (see: W. Pluta 1977):

$$
\begin{aligned}
& X_1 = a_{11}F_1 + a_{12}F_2 + \ldots + a_{1m}F_m + a_1U_1 \\
& \bullet \\
& \bullet \\
& X_j = a_{j1}F_1 + a_{j2}F_2 + \ldots + a_{jm}F_m + a_jU_j \qquad (4) \\
& \bullet \\
& \bullet \\
& X_k = a_{k1}F_1 + a_{k2}F_2 + \ldots + a_{km}F_m + a_kU_k
\end{aligned}
$$

where:

X_j – original variable (observation vector for all objects),

F_i – i-th common factor (value vector for all objects),

U_j – j-th specific factor (value vector for all objects),

a_{ji}, a_j so called factor loadings.

It is demonstrated that a factor loading a_{ji} is a coefficient of linear correlation between j-th observed standardised variable and i-th common factor. A variance of j-th variable can be formulated as a sum of squares of factor loadings from j-th row of the above system. Common factors should explain the biggest part of this variance so as to maximise so called communality given in a formula:

$$h_j^2 = a_{j1}^2 + a_{j2}^2 + ... + a_{jm}^2 \tag{5}$$

In the analysis we use reduced correlation matrix that meets a condition:

$$R' = AA^T \tag{6}$$

where the main diagonal communality estimates are placed. Other matrix elements are coefficiants of linear correlation between standardised observable characteristcs. The equation (6) is a basic relationship used to determine factor loadings.

The most popular method of factor extraction is the **principal component method**. The first factor is the one that has maximum share in common variance which means selecting appropriate factor loading values so as to maximise the following expression:

$$\sum_{j=1}^{k} a_{j1}^2 \tag{7}$$

We proceed with other factors in a similar way. The difference is that a starting point is a modified correlation matrix after eliminaing the impact of the first factor (and others). We repeat this procedure until a specific condition is fulfiled. It can be Kaiser criterion (see: G.A. Ferguson, Y. Takane 1997), which provides for the analysis of characteristic root. Only those factors are worth considering that explain more variablilities than a single variable which means that their values should exceed 1. The last stage that facilitates factor interpretation is a rotation made for instance with the use of *varimax* method that maximises variances in columns of matrices of normalised factor loadings.

Factor values can be determined as a product of factor loading matrices and standardised values of observed variables:

$$F = A^T Z \tag{8}$$

Empirical analysis that uses factor analysis and main component method was conducted for 10 characteristics observed in 22 branches of industrial processing sector for the year 2001. Table 1 gives preliminary results of the analysis i.e. characteristic roots determined for maximum number of factors (equal the number of characteristics).

Table 1. Characteristic roots and share in total component variability (results of main component method)

Component	Characteristic roots	% variance	Accumulated % variance
1	2.788	27.88	27.88
2	1.914	19.14	47.01
3	1.766	17.66	64.67
4	1.108	11.08	**75.75**
5	0.794	7.94	83.70
6	0.616	6.61	89.86
7	0.410	4.10	93.96
8	0.337	3.37	97.33
9	0.172	1.72	99.05
10	0.095	0.95	100.00

Source: Own calculations.

Table 2. Unrotated factor loadings and communality matrix

Variable	Factor				Communality
	F1	F2	F3	F4	
UPN	0.694	0.426	0.149	0.335	**0.794**
ALA	0.279	-0.644	0.578	-0.257	**0.894**
AK	0.810	-0.003	-0.288	-0.055	**0.739**
ALAK	0.330	-0.756	0.444	-0.044	**0.879**
ACO	0.771	-0.017	-0.253	-0.184	**0.693**
ARM	0.777	-0.238	-0.173	0.213	**0.736**
DBR	0.443	0.332	-0.195	-0.313	**0.441**
ZT	0.234	0.646	0.599	-0.076	**0.835**
NIM	0.074	-0.025	0.365	0.807	**0.791**
MAR	0.096	0.401	0.713	-0.304	**0.770**

Source: As same as Tab. 1.

Only first four components fulfill Kaiser criterion. Therefore four common factors are defined here. Tab. 2 shows values of factor loadings and and their square sum i.e. communality. ALA has the gratest value of communality as it is nearly 90%. The lowest value, lower by 50%, is given for DBR variable.

Interpretation of the factors was carried out with the use of varimax rotation. The trasformed factor loadings are given in Tab. 3. The bold values indicate the following connections between factors and individual variables:

F1
UPN
AK
ACO
ARM
DBR
F2
ALA
ALAK
F3
ZT
MAR
F4
Expenditure on machines and technical equipment

Table 3. Rotated factor loadings matrix

Variable	Factor			
	F1	F2	F3	F4
UPN	**0.632**	-0.149	0.419	0.447
ALA	0.035	**0.935**	0.127	-0.037
AK	**0.856**	0.055	-0.041	-0.037
ALAK	0.112	**0.918**	-0.083	0.131
ACO	**0.812**	0.101	-0.002	-0.154
ARM	**0.766**	0.236	-0.181	0.246
DBR	**0.514**	-0.193	0.228	-0.297
ZT	0.080	-0.103	**0.895**	0.134
NIM	-0.068	0.072	0.059	**0.882**
MAR	-0.099	0.162	**0.854**	-0.064

Source: As same as Tab. 1.

The interpretation of factors F2, F3 and F4 seems quite clear. F2 is a characteristic of the most automated production process since it covers whole production lines. F3 concerns financing innovative activities whereas interpretation of F4 is neutral as it relates only to one original variable. F1 due to the nature of the method used provides expalation for the largest part of communality indicating the impact of five variables of different character. This factor can be called a broad measure for technological progress.

3. Summary

The examples presented here show how to use methods for broad statistical anaylysis. However they do not exploit all possibilities of analysis of technological progress. At that stage it was a suggestion of approach where a large scope of information on manifestations of technological progress and on a range of financing it will be substituted with one (synthetic measure) or several (factors in factor analysis) characteristics that provide a comprehensive picture of the whole phenomenon. It also gives an opportunity to use non-observable characteristics in further analysis that concerns the impact technological progress exerts upon mechanisms in national economy.

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METODY POMIARU POSTĘPU TECHNICZNEGO

Autorka podejmuje próbę oceny sposobów pomiaru postępu technicznego za pomocą metod taksonomicznych i analizy czynnikowej. Przeprowadzone badania empiryczne pozwoliły na budowę syntetycznych mierników rozwoju postępu technicznego. Z kolei metoda czynnikowa wskazuje, że spośród 10 charakterystyk postępu technicznego obserwowanych w 22 branżach sektora produkcji przemysłowej tylko 4 mają istotne znaczenie dla oceny postępu technicznego.

Annex.

Values of synthetic measure for branches of industrial processing section

Branches	1999	2000	2001
Manufacture of food products and beverages	1.2332	0.6624	0.7342
Manufacture of tabacco products	1.2111	0.8480	0.6432
Textile industry	0.3868	0.4888	0.5912
Manufacture of wearing apparel and furs	0.9752	0.3239	0.4116
Manufacture dressed leather products	0.4222	0.4309	0.5294
Manufacture of wood and of products of wood	0.5944	0.7007	0.5337
Manufacture of pulp and paper	0.4739	0.4543	0.4875
Publishing and printing	0.6117	0.7121	0.5036
Manufacture of coke and refined petroleum products	1.6643	1.0175	0.8434
Manufacture of chemical products	1.2661	1.4853	1.2527
Manufacture of rubber and plastic products	0.7980	0.9678	1.1163
Manufacture of non-metallic mineral products	0.7451	1.2071	0.8172
Manufacture of basic metals	0.4744	0.3640	0.3514
Manufacture of metal products	0.9317	0.7949	0.8729
Manufacture of machinery and equipment	1.8168	1.5382	1.5925
Manufacture of office machinery and computers	1.8932	1.3192	1.1456
Manufacture of electrical machinery and apparatus	1.4961	1.2548	1.4846
Manufacture of radio equipment and apparatus	1.3308	1.3937	1.5270
Manufacture of medical instruments	2.1344	1.9789	1.7588
Manufacture of motor vehicles	1.1687	1.0806	1.1812
Manufacture of other transport equipment	1.2374	1.1560	1.2496
Manufacture of furniture and other manufacturing	1.0363	1.1669	1.1371

Source: Own calculations.